Role of household activities in peak electricity demand and distributional effects of Time-of-Use tariffs

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Abstract

Introduction of Time-of-Use (ToU) tariffs have the potential to motivate consumers to flex their energy use and, by utilising their flexibility, support the reduction in peak electricity demand. In return, lower peak demand could also reduce the system costs due to the reduced need for peaking generation and network reinforcement. By their nature, ToU tariffs would penalise consumers with high consumption during peak periods and who are not able to exercise flexibility. Therefore to ensure the affordability of energy bills it is important to understand the relationship between the timing of activities in the household and socio-demographic properties of the consumers.

This paper uses UK Time Use survey data to cluster households by their energy-related activities during the peak electricity demand periods, model the corresponding electricity demand and analyse the impact of ToU tariffs across several socio-demographic parameters. Results show that similar patterns of energy related activities exist for the clusters with different socio-demographic parameters (e.g. family structure or income). Findings also show that there is no single dominant socio-demographic parameter that defines the winners or losers from the introduction of ToU tariff.

1 Introduction

Time of Use (ToU) tariffs offer significant potential benefits to the system by enabling responsive electricity demand and reducing peaks. For example, they could reduce the need for new generation and network capacity. However, the impact of more cost-reflective pricing will vary between consumers.

In particular, those who consume electricity at more expensive peak periods, and who are unable to change their consumption patterns, could end up paying significantly more.

Understanding the distributional effects of ToU tariffs becomes vital to ensuring affordability of energy bills, at the same time as making demand more flexible. Whilst there is significant research on fuel poverty in relation to aggregate level of consumption of electricity, little is known about the effects of dynamic tariffs on different socio-demographic groups. Analysis on the distributional effects of ToU pricing is very limited and some examples are briefly reviewed here.

In a liberalised market one of the main remits of energy regulators is to ensure that vulnerable consumers are not excessively disadvantaged by changes in tariffs. In the UK, the energy regulator (Ofgem) commissioned work to understand potential distributional impacts of ToU on different socio-demographic groups of consumers. Using half hourly electricity demand data from the Energy Demand Research Project and the Low Carbon London trials, a study by Cambridge Economic Policy Associates (2017) calculated the bills that result by households based on "behavioural" estimates in response to the tariff they have selected. Findings show that there are households in all groups that would be worse off under ToU tariffs to some modest degree. According to this study, on average all socio-demographic groups, except some of the most affluent groups, would save on their annual bills. The limitations of this study relate to the use of aggregate socio-economic segmentation, which does not allow disaggregated analysis or clustering according to sets of socio-demographic variables; the uptake of tariffs based on a review of survey data rather than trials; and the use of behavioural responses from the Low Carbon London trial which is not nationally representative.

The Centre for Sustainable Energy Centre for Sustainable Energy (2014) carried out analysis of the distributional effects of ToU tariffs. This showed that most consumers would see relatively small changes in bills, but some could see increases in bills of up to 20%. However, this study did not consider the effects on different socio-demographic groups and did not consider whether households indeed had flexibility in terms of how their schedules are structured.

A review of U.S. trials Faruqui & Sergici (2013) find that low-income groups are associated with lower peak reduction than other groups. A review of pilots by Stromback et al. (2011) found that age, income, education, household size, load profile and environmental factors such as house type, house size, house age etc. are rarely captured by studies. A review by Frontier Economics & Sustainability First (2012) found no studies specifically collected information on vulnerable groups as defined by the Government's

Fuel Poverty Strategy (people with a long-term illness, families with children, disabled people and the elderly). In terms of uptake of the tariffs, stated preference studies on ToU tariffs show that age, gender, housing tenure (social renter, private renter, homeowner), employment status, education, income and social grade do not reveal any significant variation across groups (Nicolson et al. (2017)). It can be concluded that evidence on the relationship between socio-demographic variables and response to ToU tariff is not conclusive (Hledik et al. (2017)).

Based on this brief review the starting point of this paper is that the timing of people's activities plays a vital role in explaining the timing of residential electricity demand and the potential effects of ToU tariffs. The focus not only on income and other socio-economic factors, but on time use, as the timing of when electricity is used in the household is critical to understand electricity demand Torriti (2017). This approach is in line with recent interdisciplinary studies which consist of employing time use data (i.e. tracking residential users in and out of the household) and linking them to residential electricity demand based on previous work by (Wood & Newborough (2003) and Firth et al. (2008) who distinguished between deterministic and stochastic timing of appliance use. Time use data have been used before in energy demand research in the UK (Richardson et al. (2008); Richardson et al. (2010); Torriti et al. (2015)), France (Wilke et al. (2013)), Spain (Lopez-Rodriguez et al. (2013)) and Sweden (Widen & Wackelgard (2010);Widen et al. (2009)). The general approach of these studies tends to rely on either time use diary data or stochastic models. Whilst time use data have proven effective at re-generating electricity load profiles for domestic dwellings, they have never been used to infer distributional impacts of dynamic tariffs. The research work presented in the paper combines the activity-based stochastic modelling of residential electricity demand and

2 Methodology

The methodology for this paper was structured as follows:

1. Process activity data to determine number of energy related activities per household and extract socio-demographic information for each household.

2. Cluster households based on the shape of the energy-related activities profile during peak-time.

3. Identify dominant socio-demographic parameter for each cluster.

4. Populate stochastic electricity demand model with parameters for each socio-demographic group and each cluster

5. For each cluster evaluate the difference in costs between flat and ToU tariffs to identify winners and losers from ToU.

2.1 Time Use dataset

The primary source of activity data and social-demographic information for the activtiy analysis was the UK Time Use Survey (UKTUS) carried out in 2014 and 2015 Gershuny & Sullivan (2017). Several researchers and research projects have chosen the UKTUS dataset as it provides a diverse sample size of circa 16000 diaries across the UK. The survey consisted of two parts: household survey and activity dairy. Household survey provided rich socio-demographic information about the residents of the households, including the relation between the residents, family structure, household income, age of the residents, occupations, and employment status amongst others. The aim of the diaries was to capture what activities were carried out by the residents over the age of 8 years in the chosen households. Four levels of activities (primary, secondary, tertiary and quaternary) and the respondents' location were recorded at 10-minute interval over two days, a weekday and a weekend. In total there are over 270 individual activity codes that the respondents could choose from to describe their activity. To reduce the computational requirements and to focus on electricity consumption associated with activities, the activity codes were grouped by similarity (e.g. "watching sports on TV" or "watching films on DVD" grouped as "Watching TV") and whether activity is likely to be directly linked with electricity consumption. For each household, all energy related activities for each respondent to the activity diary were added together to get a profile containing the number of energy related activities in the household. For the clustering purposes the energy related profile for each household profile was normalised to per person in the household to focus the clustering on the shape of the profile.

The social-demographic information for each household was gathered form the individual survey and household survey. Combining two data sets gave a wider selection of the socio-demographic parameter for each household, contains the following information:

- Number of children in the household (variable *DM016* from UKTUS household survey).

- Overall household income (variable *Income* from UKTUS household survey).

- Property type (variable *Accom* from UKTUS household survey).

- Employment status of the residents of 16 years old and above: self-employed, employed, retired or unemployed (variable *WorkSta* from UKTUS individual survey).

- Number of residents in the full-time education (value 7 from variable *WorkSta* from UKTUS individual survey).

- Household type (variable *dhhtype* from UKTUS individual survey): single person, married or cohabiting couple with children (under 16), married or cohabiting couple without children, single parent with children (under 16), single parent without children, married or cohabiting couples in complex households, single parents in complex households and other households (e.g. unrelated or siblings).

- Number of rooms in the household (variable *NumRooms* from UKTUS household survey)

- Age of the residents (variable *DVAge* from UKTUS individual survey).

2.2 Clustering

Normalised weekday energy-related activities for each household are clustered using k-mediod method - a variation of the k-means clustering algorithm with the centroid of each cluster is selected from the existing data, instead of the mean. Clustering is performed by measuring the similarity between the half-hourly averages of energy related activities per household during the peak-demand period (from 16:00 to 20:00 on weekdays). Similarity between the energy related activities is measured using the Euclidean distance and clusters are formed based the sum of differences between each profile and the mediod profile.

The number of clusters was chosen to be 20 to maintain sufficient cluster population sizes and to facilitate group diversity of energy-related activities at peak time.

2.3 Probabilistic demand model

Demand profiles for each cluster were synthesised using stochastic high-resolution household demand model developed by McKenna & Thomson (2016). The model makes use of four-state occupancy probability and activity probabilities to generate thermo-electrical demand for a dwelling based on the given number of residents and dwelling properties.

Activity diaries from individual responders belonging to each household in clusters were analysed to generate the four-state occupancy transition probability matrix for each household size. The occupancy transition probability matrix indicates the how many residents are active and whether they are present at the property at each 10 minute period during the day.

Activities from the diaries were mapped to the six activities supported by the demand model: Watching TV, personal care, house cleaning, cooking, ironing and laundry. Similarly to the occupancy probability, diaries for each respondent belonging to the households in each cluster were used to calculate the probabilities of activities across the day and varying occupancy levels. Both occupancy and activity probabilities were generated for weekdays and weekend days using the corresponding diaries.

The demand model for each cluster was configured to generate demand for 150 dwellings. Dwelling information for the model was specified to ensure that the number of residents and the property type were representative of the households in each cluster. Each model was then run to generate 150 demand profiles for a weekday and a weekend over three seasons: summer (June, July and August), winter (December, January and February) and interseason (March, April, September and October).

2.4 Tariffs

To assess the impact of ToU tariff on each cluster of households two tariffs were chosen: standard flat tariff and price varying static tariffs. The tariff schedule and ratio of price levels for the tariffs were based on two studies by Centre for Sustainable Energy (2014) and by Hledik et al. (2017). Figure 1 depicts the timings and the price levels of the tariffs.

Three static ToU were analysed in Centre for Sustainable Energy (2014) (CSE) :

- ToU-1 is a two level tariff with peak time pricing applied daily (both weekday and weekend) between 4PM and 8PM.

- ToU-2 is a three level tariff. Peak time pricing is applied daily (both weekday and weekend) between 4PM and 8PM, mid-level pricing is applied 7AM to 4PM and 8PM to 11PM and the remainder of the time is for low price.

- ToU-3 is also a three level tariff, however, the peak-time pricing and mid-level pricing is only applied to weekdays. The ratios of the price

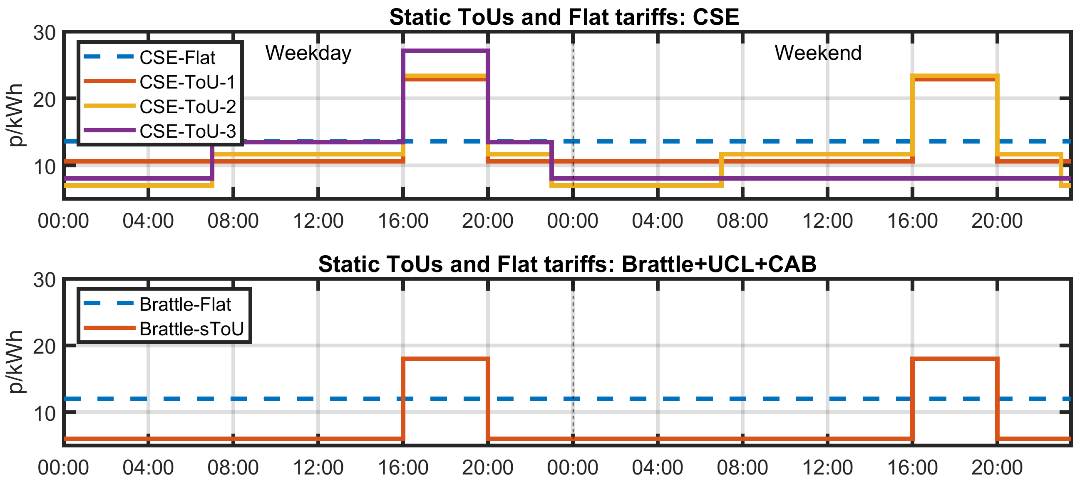

Figure 1: Flat and static ToU tariffs applied to evaluate the impact on bill costs for clusters of households.

levels is adjusted accordingly to ensure revenue neutrality [1].

Similarly to CSE ToU-2, static ToU used in Hledik et al. (2017) (hereafter refered to as Brattle-sToU) is a two level tariff with the peak time pricing applied between 4PM and 8PM daily, including weekend.

Previous works in the literature have studied the impact on ToU on the consumer behaviour and the shift in electricity demand. In this paper, it is assumed that there is no change in behaviour and in demand as result of ToU tariff. This is equivalent to assuming that there is no significant difference across socio-demographic groups in terms of response to changes in tariffs.

3 Results and discussion

3.1 Clustering

Statistical information for the profiles of energy related activities for each cluster are shown in figure 2.

Mean energy related activity profile per cluster generally follows the shape of residential demand profile: some activity around mid-night, very little activity at night and morning peak around 7-8 AM. During the day the

[1]Applying a ToU tariff to the Elexon standard demand profile class 1 must result in the same annual cost as a standard tariff.

number of activities per person vary between clusters, predominantly between 0.2 and 0.3, except for cluster 20.

Because the households were clustered on the shape of activity profiles during the peak time, several distinctive groups of peak time activities are visible. Most of the clusters have peak time high number of energy related activity per person that start at the beginning of peak time or during and slowly drop off around 10 PM.

For majority of the clusters the standard deviation (s.d.) remains similar throughout the day, again, except for cluster 20. Over all the s.d. remains high for most clusters, even in the peak period, indicating high diversity of energy related activities within clusters. During the peak time, the s.d. is expected to drop due to the clustering of the activities during peak time by the similarity of their shape. The diversity within clusters can be explained by the fact that the clustering is performed on half-hourly average of 10-minute energy related activities, which allows for variation of energy-related activities during the peak time at 10 minute resolution.

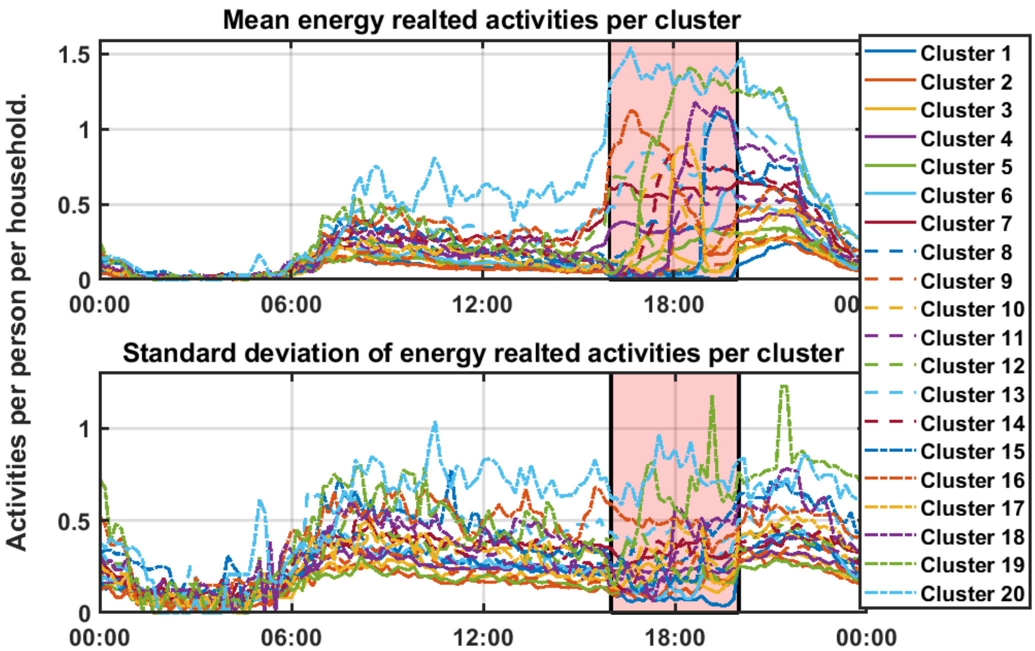

Figure 2: Mean and standard deviation of energy related activities at 10-minute resolution per resident per household for each cluster. Red-area indicates the period of peak electricity demand.

Figure 3 depicts the number of households in each cluster. Cluster 1 contains 772 households (18% of the population) and is almost double the size of any other cluster. The smallest two clusters 19 and 20 contain 65 and 61 households, respectively.

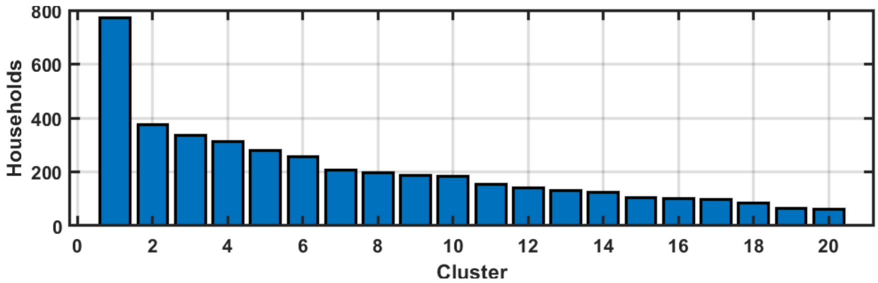

Figure 3: Number of households per cluster.

3.2 Sociodemographic distribution

Figure 4 demonstrates the proportion of types of families in each cluster. Most of the clusters are have similar share of single person and married/ cohabiting parters without children as the entire population of households in the survey. Exceptions are clusters 8, 12, 13, 14, 18 and 19, where proportion

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Single	27.29	26.25	28.46	30.21	28.99	25.09	29.88	30.69	21.16	31.46	29.21	26.85	22.79	25	16.81	27.72	34.02	30.53	21.69	22.22	30.51
M/C w chldrn	17.46	16.23	19.78	17.52	18.89	16.97	20.32	13.86	15.34	16.29	16.29	19.46	13.24	13.71	24.37	15.84	17.53	22.11	16.87	19.05	20.34
M/C wo chldrn	29.24	30.87	30.08	29.61	28.66	25.46	25.1	27.23	32.28	25.84	29.78	27.52	38.24	33.87	32.77	23.76	23.71	21.05	37.35	34.92	25.42
SP w chldrn	4.877	4.354	4.336	3.625	4.235	3.69	5.179	5.446	5.82	4.494	6.18	5.369	4.412	5.645	4.202	8.911	5.155	7.368	7.229	1.587	10.17
SP wo chldrn	2.857	3.562	3.252	2.417	2.932	2.214	3.984	1.485	2.646	3.933	2.809	3.356	4.412	2.419	1.681	2.97	1.031	1.053	2.41	1.587	0
M/C in complex hh	8.645	9.103	6.775	6.647	8.469	12.55	8.367	9.901	9.524	10.67	7.865	8.725	7.353	5.645	10.08	6.931	10.31	7.368	4.819	15.87	5.085
SP in complex hh	5.616	5.145	3.794	4.532	4.886	8.487	3.984	6.436	7.407	3.371	6.18	6.711	7.353	10.48	5.042	8.911	4.124	7.368	3.614	1.587	8.475
Other	2.98	3.166	2.71	4.23	2.606	3.69	1.992	2.97	4.762	3.371	0.5618	1.342	2.206	1.613	5.042	4.95	3.093	1.053	4.819	3.175	0

Figure 4: Proportion of cluster consisting of family types: single, married/ cohabiting couple with children, married/cohabiting couple without children, single parent with children, single parent without children, married/cohabiting couple in complex household and single parent in complex household.

of married/cohabiting couples without children dominates the proportion of single residents. Whereas, clusters 6, 9, 15, 16, 17 and 20 are predominantly populated by residents who are single.

Employment proportions per cluster are shown in figure 5. Similarly to the family structures, the proportion of employment statuses for a majority of the clusters has similar breakdown as for the entire population used in the study. At least 33% (cluster 18) are employed across all clusters , with the highest employment (over 44%) is present in clusters 3,13,14,17 and 19.

Retired proportions range between 15.15% and 27.32%. Clusters with lowest retired proportions are 15 and 17, and highest retirement is clusters 8, 18 and 20.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Empl.	41.47	43.26	37.57	44.32	42.91	41.1	41.78	39.64	38.99	39.77	39.48	42.21	39.24	44.4	44.32	42	38.83	44.51	33.76	44.06	42.86
Self-Empl	7.544	7.803	6.63	6.08	8.277	7.117	9.736	6.218	6.366	9.51	8.069	9.74	5.903	6.8	6.061	8.5	8.511	7.143	12.1	5.594	4.464
Retired	22.07	22.18	25.28	23.84	20.61	20.82	20.08	23.83	27.32	21.61	22.19	20.45	22.22	20.8	15.15	17	21.81	18.68	26.11	18.88	26.79
Study	6.495	6.571	6.215	5.92	5.405	9.431	4.462	6.218	7.162	7.493	4.323	7.143	6.597	6.8	6.061	9	6.915	6.593	7.643	7.692	2.679
Unempl	3.21	2.601	3.729	3.52	1.858	2.135	2.637	4.922	3.448	4.323	4.899	2.922	2.778	5.2	3.788	5.5	2.66	1.099	1.274	4.895	2.679
MatLeave	0.6245	0.6845	0.4144	0.8	0.6757	0.1779	0.2028	0.5181	0.7958	0.5764	1.153	0	0.6944	1.2	1.515	0	1.064	1.648	0.6369	0	0
Homestay	4.796	4.654	5.11	3.36	5.405	4.626	6.491	4.145	3.448	4.035	5.764	4.221	5.556	4.4	4.924	4.5	6.383	3.846	7.643	4.196	5.357
Sick/disabled	2.173	1.711	1.934	2.4	1.689	3.915	1.014	2.073	2.387	2.017	2.305	1.623	4.861	1.2	3.03	3	2.128	1.099	2.548	2.098	1.786

Figure 5: Proportion of cluster by employment of residents in the cluster: employed, self-employed, retired, studying and unemployed. (Statuses not shown: on government training scheme, unpaid worker in family business and doing something else.

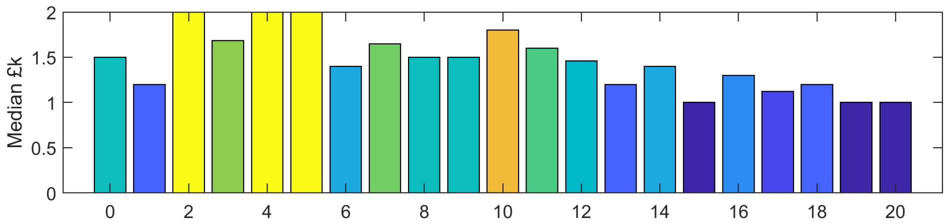

Figure 6: Median monthly household income for the households in each cluster.

The following plots show median household income per cluster (figure 6), median number of residents per household in each cluster (figure 7), median number of rooms per household in each cluster (figure 8) and median age of the residents in each cluster (figure 9).

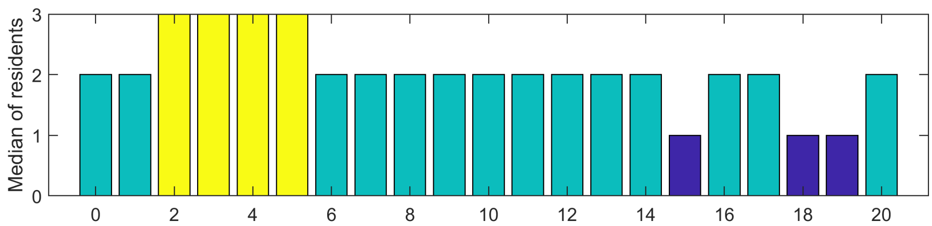

Figure 7: Median number of residents per household in each cluster.

Clusters 2, 4 and 5 show same values for median income, median number of residents and median number of rooms in the household. However, the shape of the mean energy related activities for these clusters during the peak-time is dissimilar. This could suggest that these socio-demographic parameters do not influence the timing of increase in energy related activities during the peak-time period.

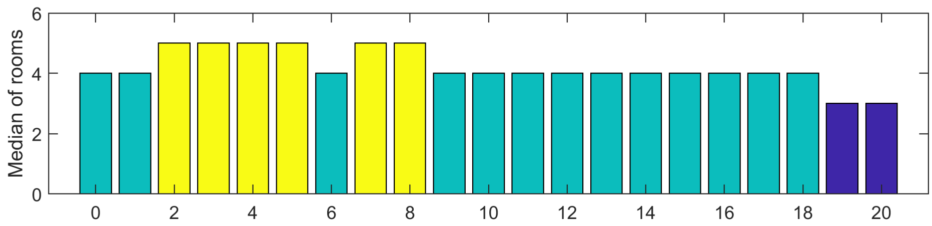

Figure 8: Median number of rooms per household in each cluster (values for variable *NumRooms* in UKTUS household dataset).

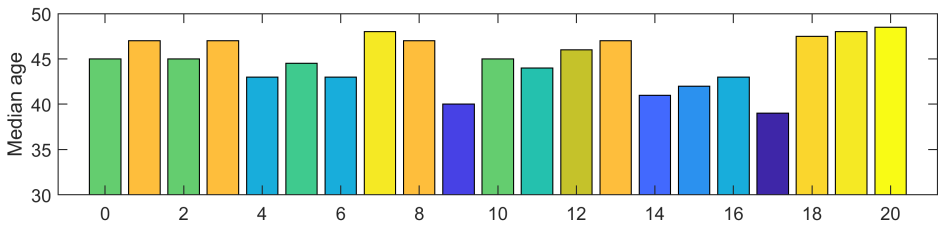

Figure 9: Median age of the residents in each cluster.

On the other end of the spectrum, lowest median income and smallest median number of rooms are present in clusters 19 and 20. Furthermore, the median age for these clusters is above 48. Mean energy-related activities for these clusters is also the two highest during the peak-time.

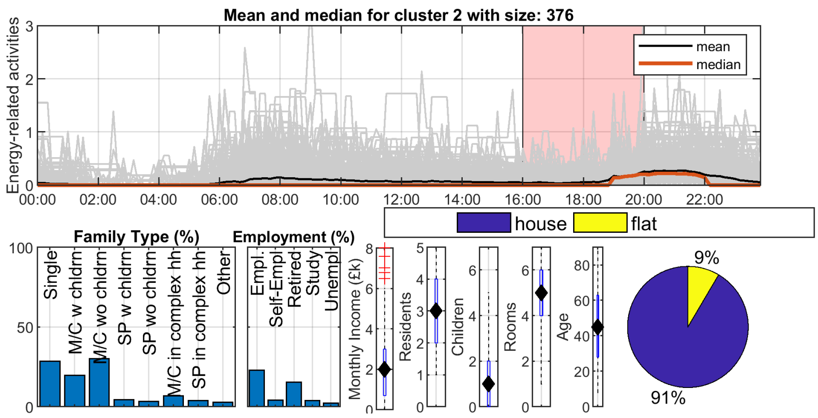

Figure 10: Energy related profiles and the sociodemographic information for the households in cluster 2.

Figures 10 to 13 show the socio-demographic breakdown of individual clusters along with their energy-related profiles.

Taking a closer look at clusters 2 and 5 in figures 10 and 11 shows that although the distribution of social-parameters is similar, the timing and the intensity of rise in energy-related activities during peak-time is different. The period of high density energy-related activities is wider and starts earlier in cluster 5 compared to cluster 2.

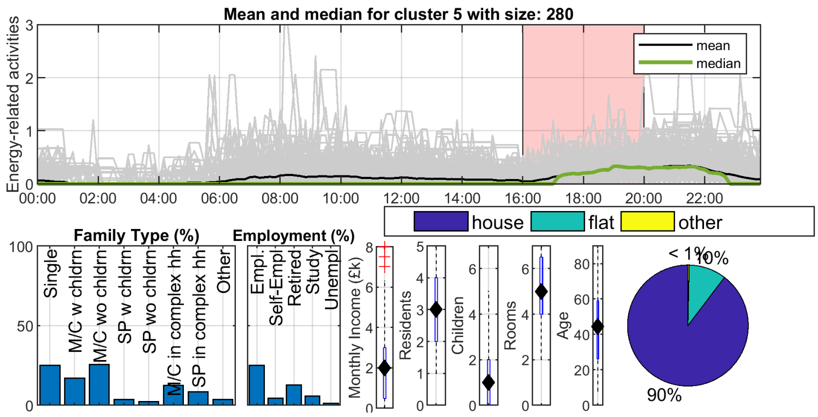

Figure 11: Energy related profiles and the sociodemographic information for the households in cluster 5.

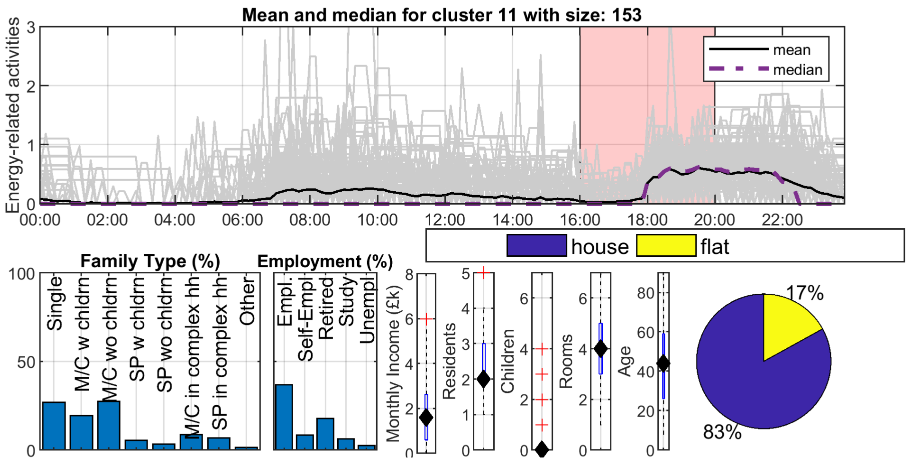

Figure 12: Energy related profiles and the sociodemographic information for the households in cluster 11.

Cluster 11 (figure 12) has lower median income, median number of rooms and number of residents than clusters 5 and 2. Age distribution in cluster 11 is similar to cluster 5, yet is cluster 11 the median number of children is zero compared to clusters 2 and 5. Against the distribution of socio-demographics, the profile of energy related activities for cluster 11 has higher density during the day and sharper increase during the peak time around 6PM.

Figure 13 shows the smallest cluster but with the highest median age. Notably, the number of energy related activities throughout the day and the evening for this cluster is significantly higher than any other cluster.

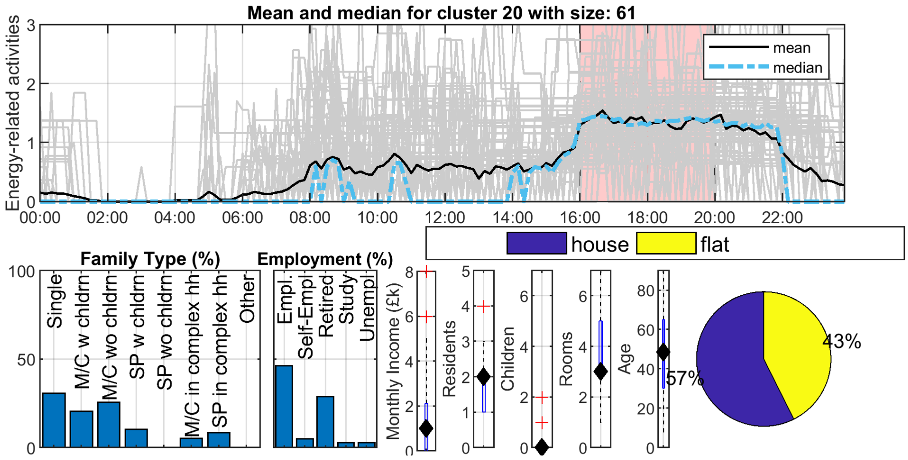

Figure 13: Energy related profiles and the sociodemographic information for the households in cluster 20.

3.3 Electricity demand modelling

Figures 14 and 15 show the statistical overview of 150 demand synthetic profiles.

Diversity of the demand profiles for the clusters demonstrates that the grouping of the energy-related activities during the peak time leads to varying timing and magnitude of peak time electricity demand. For example the shape of the inter-quantile range corresponds to the timing of increase in energy related activities. Clusters 2 and 5 spikes in the upper 75^{th} quantile correspond to the grouping of the energy related activities in figures 10 and 11.

In addition to particular patterns during peak-demand period, individual clusters also demonstrate diversity in the shapes of the morning peaks.

Clusters 10, 12, 13, 15, 18, 19 and 20 have very distinctive sharp morning peaks. Whereas, clusters 3, 4, 5, 7, 8, 16 and 17 have prolonged morning demand period. Such link between morning and evening peaks perhaps could be an indicator of how routines and sequences of activities contribute to the shape of demand profiles.

Figure 15 show similar picture for the weekend demand.

Another important point to note is the relationship between the mean, median and the inter-quantile range. Overall the synthetic demand is skewed towards the lower values throughout the day because the median is lower than the mean. For the most of the clusters, there is greater variability in

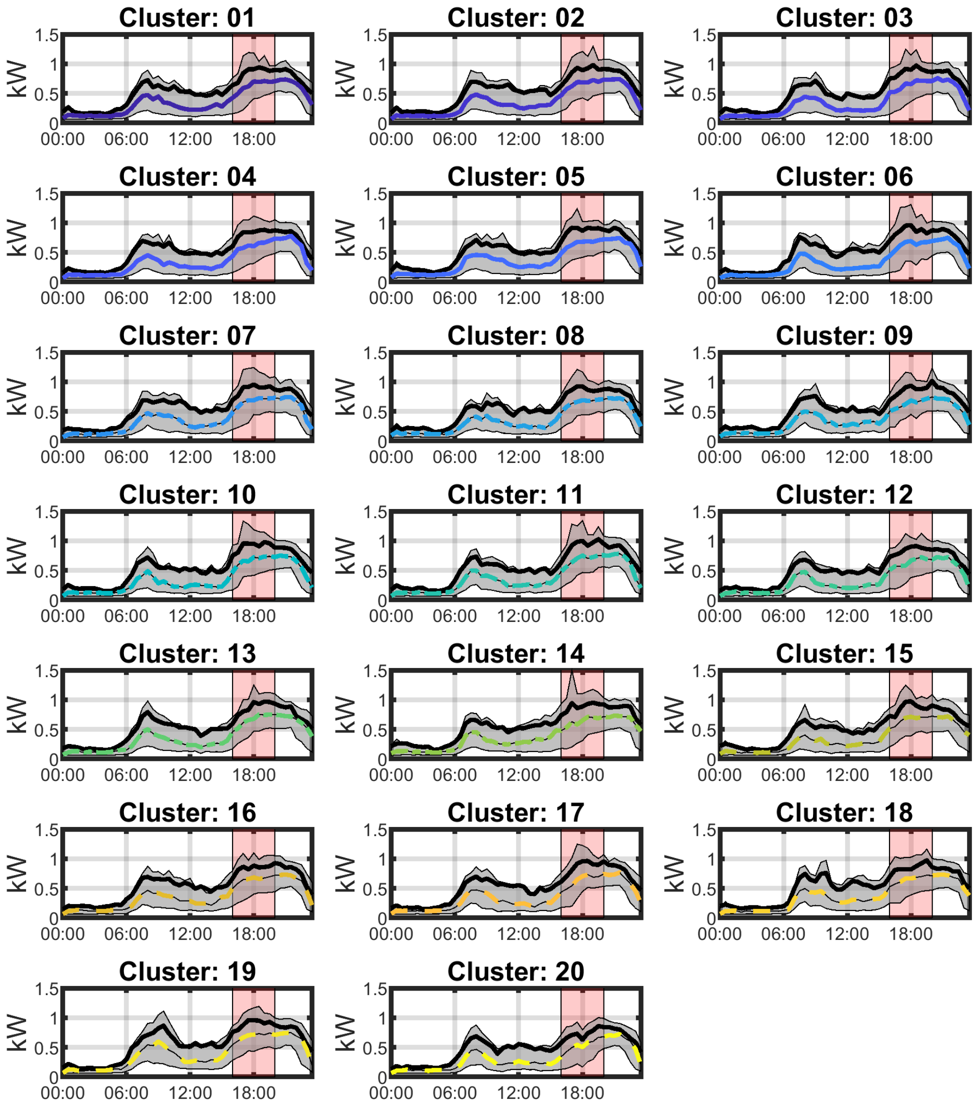

Figure 14: Mean (solid thick line), median (coloured line) and inter-quantile range of 25^{th} and 75^{th} quantiles (grey area) of synthetic demand profiles generated by CREST model based on activity probabilities from diary population of each cluster. Time period: weekday during winter period.

the morning and evening peaks as suggested by the distance between the mean and the upper 75^{th} quantile. This variability can be explained due to the normalisation of energy-related activity profiles per resident at the clustering stage. As the results, households with greater number of residents and higher demand could be clustered with smaller households.

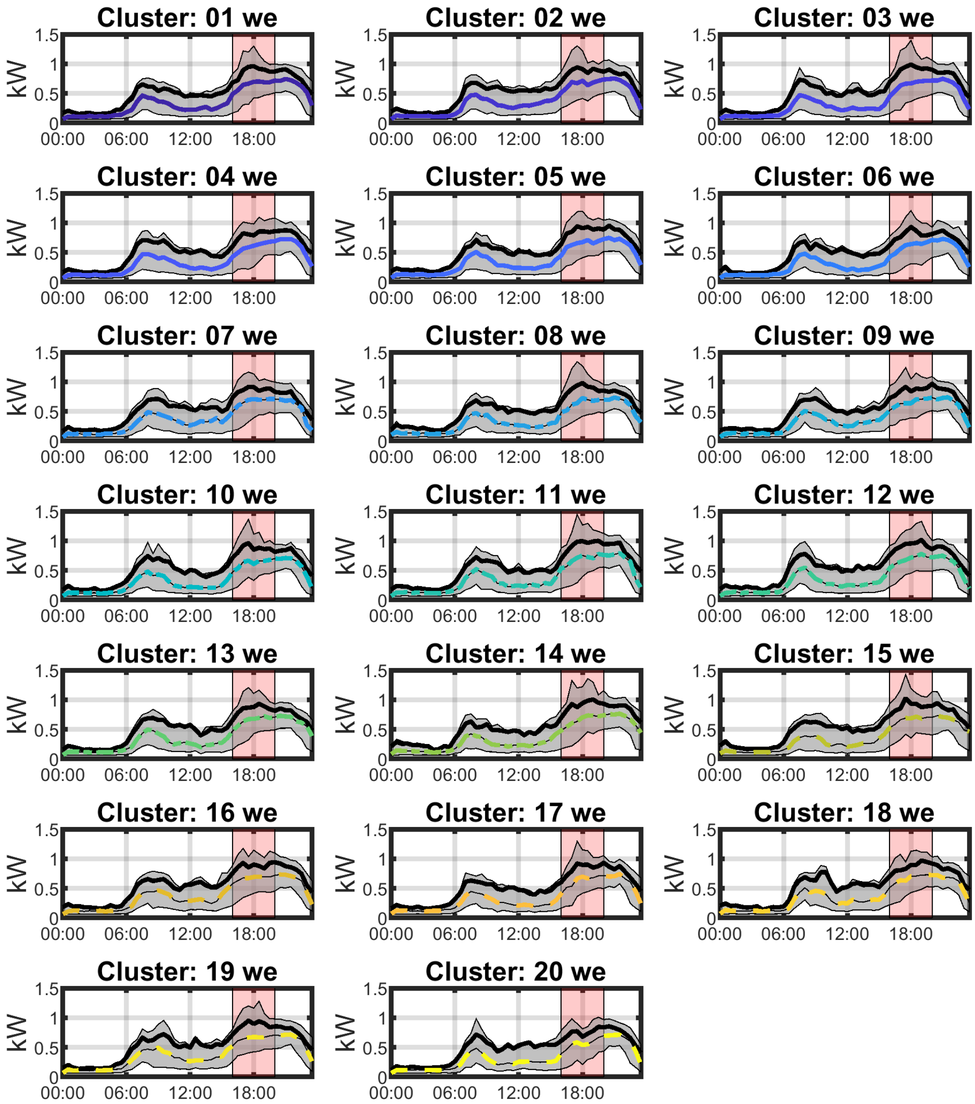

Figure 15: Mean (solid thick line), median (coloured line) and inter-quantile range of 25^{th} and 75^{th} quantiles (grey area) of the synthetic demand profiles generated by CREST model based on activity probabilities from diary population of each cluster. Time period: weekend during winter period.

3.4 Distributional ToU impact

The net impact on the bill of each 150 synthetic demand profiles in each cluster across all seasons and for each type of selected ToU profiles are presented in figures 16 to 19.

Applying CSE-ToU-1 gives a spread of -5% to +5% around the median for most of the clusters. Median and inter-quantile range of the impact on the bill is predominantly below zero, indicating that most of the dwellings in most of the clusters would benefit from the SCE-ToU-1 tariff. However, clusters 4, 9 and 20 have median above the zero line. Most of the dwellings in cluster 20 will be disadvantaged from switching to CSE-ToU-1 from the CSE-flat tariff. On the other end, most of the cluster 11 would benefit for the CSE-ToU-1.

In figure 17, unlike with CSE-ToU-1 tariff, most of the dwellings for all clusters would benefit by switching to CSE-ToU-2 from CSE-flat tariff. Similarly to CSE-ToU-1, clusters 9 and 20 are the least to save on the bill.

Quite a different picture is depicted in figures 18 and 19 where all dwellings in all clusters will pay more as result of switching to ToU. Difference is ratios between the price levels (and number of prices levels) between CSE-ToU-3 and Brattle-sToU have an impact on the magnitude of change on the bill. With CSE-ToU-3 range of bill increase is between 3% and 20% , whereas for Brattle-sToU the increase is significantly higher, 17% to 33%.

Despite the overall increase from CSE-ToU-3 and Brattle-sToU, there are clusters which are affected less than others. To highlight the difference between clusters and remove the impact of absolute price levels, figure 20

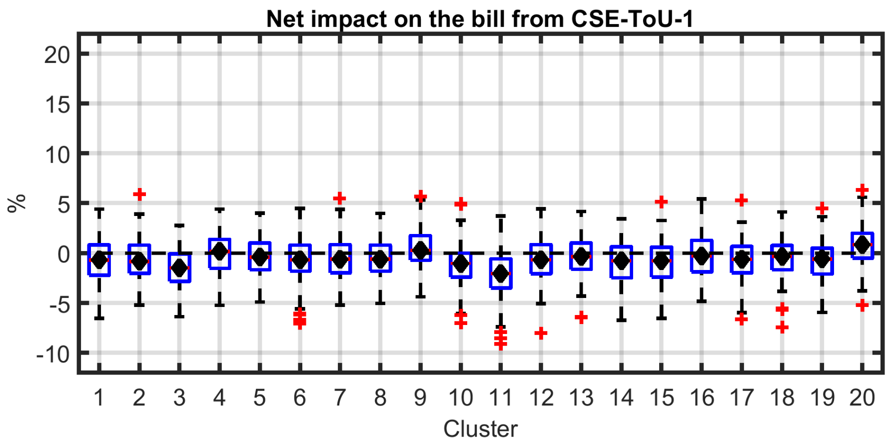

Figure 16: Distribution of net impact on the bill for demand profiles in each cluster with CSE-ToU-1 tariff compared to standard tariff .

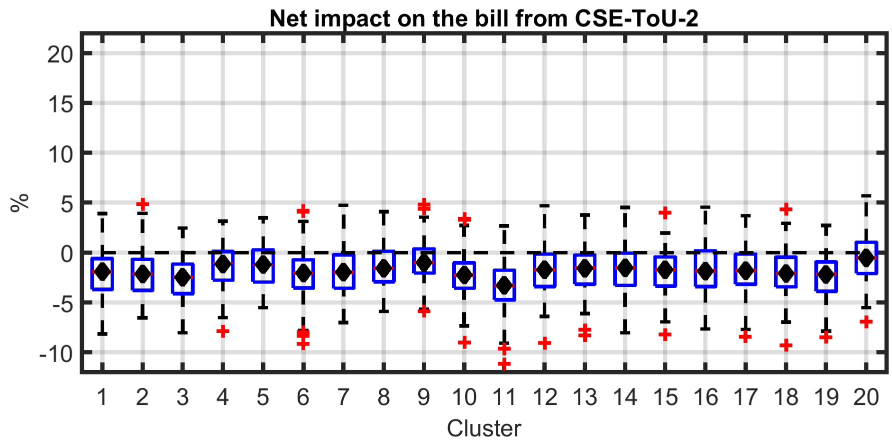

Figure 17: Distribution of net impact on the bill for demand profiles in each cluster with CSE-ToU-2 tariff compared to standard tariff .

shows the residual mean of net bill impact for each ToU for each cluster. Residual mean was calculated by subtracting the mean bill impact from the net bill impact in all clusters for the corresponding ToU tariff.

Relative difference between the clusters shows that residents from clusters 3 and 11 are average winners from ToU in comparison to other clusters, particularly from ToU with the same price levels for weekday and weekends (CSE-ToU-1, CSE-ToU-2 and Brattle-SToU). Clusters 9 and 20 are, on the contrary, losers such ToU tariffs. CSE-ToU-3 appears to reduce the difference between the clusters due to the the continuous low-price period during the

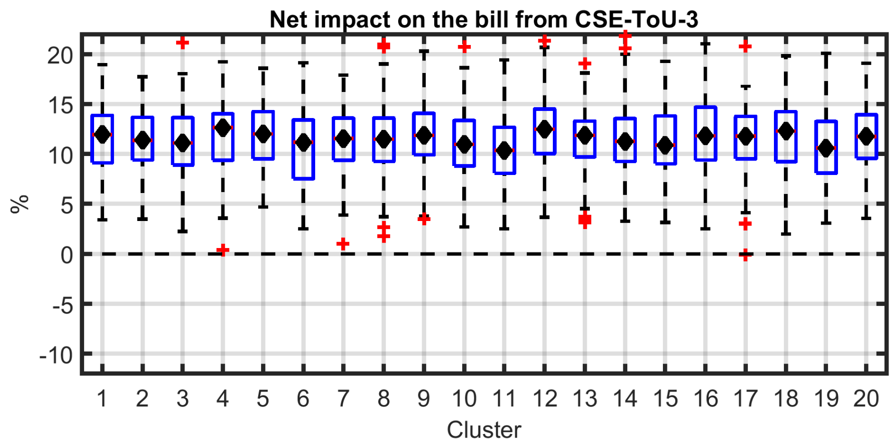

Figure 18: Distribution of net impact on the bill for demand profiles in each cluster with CSE-ToU-3 tariff compared to standard tariff .

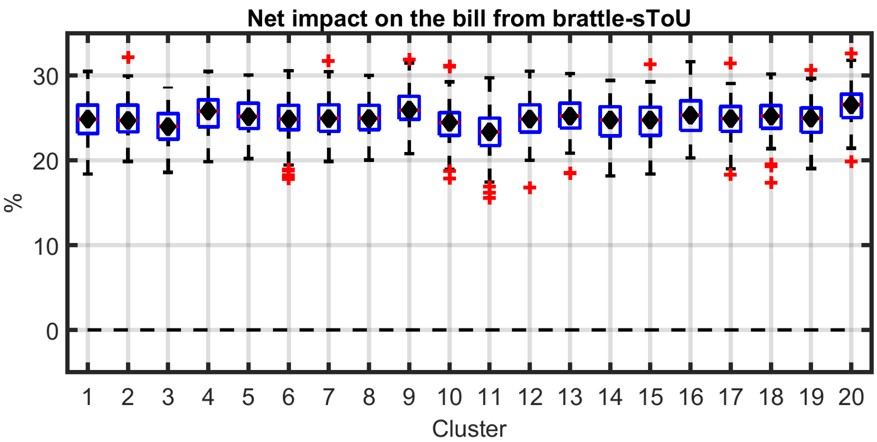

Figure 19: Distribution of net impact on the bill for demand profiles in each cluster with Brattle-sToU tariff compared to standard tariff .

weekend.

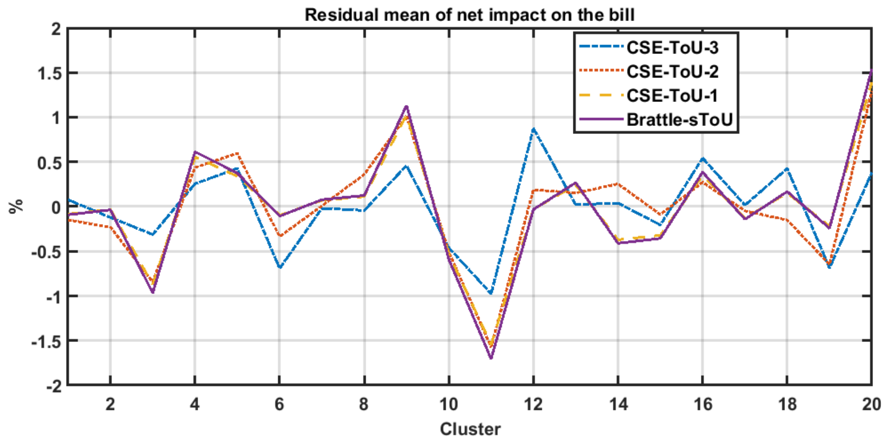

Figure 20: Residual mean of impact on the bills per cluster for the chosen ToU tariffs.

Comparison of socio-demographic parameters does not reveal a dominant parameters responsible for the impact on the bill. Clusters 2 and 5 have similar socio-demographic distribution, yet cluster 2 tend to be worse off on average compared to cluster 5 for all ToU tariffs. Cluster 20 continuously demonstrated negative impact on the bill and have a distinctive socio-demographic parameters (highest median age and lowest median income). However, the cluster size is relatively small which undermines the significance.

4 Conclusions

Time of use tariffs are designed to encourage consumers to exercise their flexibility and shift their consumption away from times when the demand on the network is high (so called peak periods). From an economic perspective the effectiveness of the ToU tariffs is in price of electricity that is constrained by energy users ability and motivation to change consumption based on price signals. Social science researchers would argue that the engagement of consumers with dynamic tariffs depends on the way to which everyday life and household rhythms can be aligned with the new tariffs.

The objective of this paper was to understand the distributional impact of ToU tariffs through analysis of household activities and the modelling of electricity demand. Clustering of energy-related activities in households have demonstrated distinctive patters in the evening peak periods. However, socio-demographic distribution for each cluster did not demonstrate a significant dominant parameter (e.g. work status, income, family structure) being linked to the shape or intensity of the energy-related activities during the peak-time.

In addition to identifying clusters with similar evening energy-related activities, the resultant clusters of households also demonstrated distinctive patters in density and timing of energy-related activities in the morning. The link between variation in morning and evening patterns of energy-related activities suggests that energy consumption activities are not evenly spread in everyday life and they are influenced by institutional rhythms.

Occupancy and activity probabilities for each household in each cluster were used to generate synthetic electricity demand profiles for each cluster. Across the clusters, synthetic demand profiles demonstrated variability in electricity demand aligned with the changes in energy-related activities during the peak time. Despite the variability within the inter-quantile range, the overall median and mean electricity profiles for all clusters are similar. This finding could be a sign of synchronisation across the society: people do similar things at peak time regardless of their socio-demographic status.

Comparison of several ToU tariffs also did not demonstrate a significantly dominant single socio-demographic parameter defining the impact of the ToU. Results confirmed that the ratio between high and low price levels strongly influences the overall impact of ToU across all clusters. In line with previous studies of smart meter data and ToU tariffs, Comparison of residual mean impact (or relative difference between clusters) showed that ToU where weekends have low price level reduce the difference in impact of ToU between clusters.

The next step in the analysis of distributional impact of ToU tariffs is to restructure socio-demographic information in to combinations of values and parameters (e.g. single parent in full-time employment with two children living in a flat within Greater London).

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Keywords— Energy Demand; Energy Economics; Energy Consumer Domestic; Energy Modelling; Energy Policy.